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China containerised freight index forecast: A comparative study based on machine learning

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Abstract: The Chinese commodity futures market has become an essential component of the global maritime transport system as international trade continues to expand. The China Containerised Freight Index (CCFI) serves as a valuable indicator of the maritime industry's health and is highly sensitive to fluctuations in the Chinese commodity futures market. However, there is a lack of research utilizing Chinese commodity futures prices as predictors for the CCFI. This study analyzes a dataset comprising 29,308 observations collected daily from March 24, 2017, to May 27, 2022. We conduct a comparative analysis of CCFI prediction using Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and a hybrid CNN-LSTM model. The CNN-LSTM model effectively identifies nonlinear features within CCFI data and captures the long-term dependencies of the index over time, as evidenced by our results. This model outperforms the individual CNN and LSTM approaches and demonstrates high adaptability to fluctuations arising from random sample selection, data frequency, and structural discontinuities within the sample population. This study highlights the potential of machine learning methods for forecasting shipping indices, thereby enhancing understanding of the relationship between the shipping industry and financial markets. The findings provide logistics companies, shipping organizations, and governments with robust risk management and decision-support tools.

Keywords: CCFI forecast, futures market, machine learning, convolution neural network, long and short-term memory

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1 Introduction

The container shipping industry is a critical component of global trade integration, facilitating the large-scale movement of international goods and significantly influencing the efficiency and stability of global supply chains. Freight rates in this sector are highly volatile, primarily driven by fluctuations in the demand for transport services and the supply of capacity. These rates are of paramount importance to all stakeholders involved in international maritime trade, including shippers and carriers, and play a central role in container shipping costs. Therefore, the ability to accurately predict future fluctuations in container freight rates is essential for informed decision-making. The China Container Freight Index (CCFI) is a vital tariff and price indicator in the shipping sector, widely recognized for its capacity to accurately reflect economic activity dynamics. The CCFI serves as a key metric for evaluating the health of the shipping industry, global trade dynamics, containerized transport, and the balance between supply and demand.

In the context of economic globalization, the Chinese futures market has emerged as a critical component of the global maritime financial ecosystem. Commodity prices in the Chinese futures market significantly impact the shipping industry. The Chinese futures market is closely linked to the CCFI, a crucial indicator of container shipping market conditions, and is highly sensitive to its fluctuations (Mo et al., 2017). Fluctuations in the CCFI are significant factors in the volatility of futures market prices, affecting market sentiment and investor expectations (Kang and Yoon, 2019). Investors and financial analysts frequently use shipping indices such as the CCFI as economic indicators to anticipate changes in commodity markets, stocks, and other financial markets. Concurrently, bulk carrier owners, charterers, and other transport entities increasingly rely on the CCFI for decision-making when formulating strategies and executing business plans. Consequently, a comprehensive understanding of the relationship between the futures market and the CCFI is essential for developing effective investment risk management strategies and accurately predicting market dynamics (Prokopczuk, 2011).

In recent years, an increasing number of studies have focused on the forecasting of the CCFI, recognizing it as a non-stationary, nonlinear time series influenced by a variety of complex variables (Charfeddine et al., 2019; Huo and Ahmed, 2018). However, early studies primarily employed causality-based econometric models for CCFI forecasting, which require a certain level of regularity and smoothness in the input data. Additionally, the accuracy of these econometric models is susceptible to significant errors due to the characteristics of CCFI data. Research has shown that AI-based methodologies offer numerous advantages over conventional statistical and econometric models (Cartwright and Riabko, 2015). As a result, researchers have begun to implement artificial intelligence (AI) methodologies, including artificial neural networks (ANNs), long short-term memory methods (LSTMs), and nonlinear regression analyses, to forecast the CCFI. Thus, accurately predicting the CCFI is imperative for maritime business stakeholders to mitigate market risk and engage in strategic planning. This paper poses two fundamental research questions: Which forecasting model can enhance the accuracy of CCFI forecasts?

To address these research questions and fill the gap in CCFI prediction research, this study conducts a comparative analysis using CNN, LSTM, and CNN-LSTM models. This investigation utilizes a dataset comprising 29,308 daily observations from March 24, 2017, to May 27, 2022. The results indicate that the CNN-LSTM model effectively identifies nonlinear properties and captures complex fluctuations in CCFI data. In the CCFI prediction task, this model outperforms both the individual CNN and LSTM models, achieving an R^2 value of 71.68%. It provides a more accurate representation of the dynamics of the shipping market.

This paper makes several contributions. First, it compares the machine learning models of CNN, LSTM, and CNN-LSTM from a machine learning perspective, enhancing the accuracy of CCFI predictions and broadening the scope of machine learning research. It also offers valuable insights for the application of machine learning in the field of CCFI. Second, this study expands the application of machine learning methods within the realm of shipping finance, demonstrating the significant potential of the Chinese futures market in forecasting the global shipping index. Additionally, it provides a novel perspective on the intricate relationship between the Chinese financial market and the shipping industry. Lastly, the model's applicability is not limited to CCFI forecasts; it can also be employed to track recent advancements in the shipping finance sector or extended to include forecasts of other indices. This capability allows stakeholders to modify their portfolios and operational strategies in real time, fostering sustainable business development and maintaining the overall stability of financial markets.

The subsequent sections of this investigation are summarized as follows: Section 2 reviews the CCFI forecasting methodology and the relevant literature on Chinese futures. Section 3 details the data and integration methodology employed. Section 4 examines and contrasts the primary empirical findings. Finally, Section 5 summarizes and discusses the results, while Section 6 delineates the study's limitations and offers suggestions for future research.

2 Literature Review

2.1. CCFI Forecasting Study

The China Container Freight Index (CCFI) was introduced by the Shanghai Stock Exchange (SSE) in 1998 to address the rapid expansion of China's container shipping market and to provide a standardized tool for predicting and measuring fluctuations in freight rates (Kang and Yoon, 2019). The CCFI encompasses both spot and contract freight rates, with data sourced from the voluntary contributions of 22 reputable companies with significant market shares (Bosch and Pradkhan, 2015). This includes a diverse range of organizations, from small businesses to major policymakers involved in containerized trade (Bohl et al., 2021). The CCFI reflects the overall level of freight rates in China's export container market, as reported by ten Chinese hub ports: Dalian, Tianjin, Qingdao, Shanghai, Nanjing, Ningbo, Xiamen, Fuzhou, Shenzhen, and Guangzhou. Given the prominence of these ports in global container throughput rankings and their inclusion in outbound container service rotations from the Far East (FE), the CCFI serves as a fair representation of the region as a whole (Prokopczuk, 2011). Furthermore, globally recognized liner companies, including CMA-CGM, Hamburg Line, COSCO, Maersk, and Hapag-Lloyd, also contribute data to the CCFI (Prokopczuk, 2011). As a result, the CCFI is highly regarded within the container shipping industry and is frequently utilized as a base asset in forward rate agreements or as a floating element in index-linked container contracts, thus making it a critical freight indicator for global container trade. It is considered the second most effective freight rate index globally, following the Baltic Dry Index (BDI) (Bosch and Pradkhan, 2015). Consequently, the CCFI is regarded as a barometer of the Chinese shipping industry.

Despite the existence of other container freight indices, such as the Global Container Index (WCI) released by Drewry in 2021, the Ningbo Container Freight Index (NCFI) from the Ningbo Shipping Exchange (NSX), the Baltic Global Container Freight Index (FBX), and the recent Xeneta Shipping Index (Bohl et al., 2021), the CCFI has garnered significant attention in the academic community. Recent years have seen an increase in comprehensive research on the CCFI. Chen et al. (2021) proposed a forecasting model that integrates empirical modal decomposition with grey-wave forecasting methods, which are predicated on the CCFI. Their model divides the time series into long-term trends and short-term cycles, forecasting the trend period using a generalized GM and the cycle period using a grey wave forecasting model. The findings indicate that this hybrid model significantly enhances forecasting accuracy, providing valuable decision support for practitioners hedging risk through forward rate agreements. Additionally, Schramm and Munim (2021) explored the potential of the autoregressive integrated moving average (ARIMA) multivariate modeling framework, incorporating soft-survey-generated sentiment and confidence information as variables to predict the performance of the CCFI. Their study employed exogenous variables (ARIMAX) and vector autoregression (VAR), concluding that the forecasting accuracy of ARIMAX is significantly higher than that of the basic ARIMA model when combined with soft factual information. Nevertheless, only a limited number of studies have established a connection between the CCFI and the Chinese futures market.

2.2. Futures Market Research

China's commodity futures market holds a crucial position in the global economy, providing participants with multiple functions, such as price discovery, risk management, and investment speculation (Bosch and Pradkhan, 2015). It has significantly impacted economic stability, financial innovation, and market efficiency (Mo et al., 2017). With growing academic interest in commodity futures markets, the interconnections between China's futures financial markets and various other markets have been widely studied (Kang and Yoon, 2019). One central theme in futures market research is price volatility analysis, as volatility is a key factor influencing trading decisions and risk management strategies. Existing studies have employed various statistical and econometric models to examine the drivers of price volatility in futures markets, covering areas such as futures and freight (Prokopczuk, 2011), futures and stock markets (Huo and Ahmed, 2018), futures and energy (Charfeddine et al., 2019), futures and agricultural products (Cartwright and Riabko, 2015), and futures and metals (Bosch and Pradkhan, 2015), among others.

Another area of interest in futures market research is market efficiency. Researchers have focused on analyzing the operational efficiency of futures markets by examining factors such as regulatory reforms, speculative behavior, and information efficiency (Bohl et al., 2021; Mohanty and Mishra, 2020). Bandyopadhyay and Rajib explored the asymmetric relationship between the Baltic Dry Index (BDI) and commodity spot prices (Bandyopadhyay and Rajib, 2023). These findings provide valuable insights into the information content of futures prices and potential opportunities. Furthermore, the impact of external factors on futures market behavior has garnered research interest, including macroeconomic indicators, policy changes, and technological advancements. Some studies have examined the effects of these factors on futures market volatility, price discovery, and liquidity (Siami-Namini et al., 2019).

In recent years, there has been an increased focus on applying machine learning algorithms to futures market research. Techniques such as neural networks and ensemble methods have been employed to identify patterns, predict futures price movements, and develop automated trading strategies (Bandyopadhyay and Rajib, 2023). These algorithms have demonstrated promising results in terms of prediction accuracy and robustness. For instance, Siami-Namini et al. (2019) conducted a study on forecasting stock indices from six different markets and compared the performance of ARIMA, LSTM, and BiLSTM models, finding that the use of BiLSTM significantly improved forecasting accuracy. Lin et al. (2022) utilized a deep learning (DL) denoising technique combined with a BiLSTM-Attention-CNN model to predict crude oil futures prices, showing that the combined model performed more accurately than any single model. However, few studies have investigated the interaction between the CCFI and Chinese futures markets, and there remains a gap in research linking the CCFI with the Chinese commodity futures market. Therefore, to examine the linkage between the CCFI and the Chinese commodity futures market, we propose a deep learning integrated model using CNN-LSTM to predict the CCFI utilizing big data from the Chinese commodity futures market.

3 Research Methodology

3.1 Data Description

The models in this study are developed using two discrete datasets: the China Container Freight Index (CCFI) data, the Clarkson Average Container Ship Earnings (CACE), and the Shanghai Container Freight Index (SCFI) data obtained from the Shanghai Shipping Exchange and Clarkson Shipping Company, respectively. The China Commodity Futures dataset encompasses trading prices of commodity futures on China's four most renowned trading platforms: the China Financial Futures Exchange, the Shanghai Futures Exchange, the Dalian Commodity Exchange, and the Zhengzhou Commodity Exchange. The dataset includes daily data from March 24, 2017, to May 27, 2022, totaling 29,308 observations. These extensive sample datasets provide a sufficient amount of input data for training, testing, and evaluating the CNN-LSTM integrated model.

In this study, the dependent variable is the CCFI, while the independent variables include the following: Clarkson Average Container Ship Earnings (CACE), Shanghai Containerized Freight Index (SCFI), Rebar Futures (RB), Copper Electrode Futures (CU), Gold Futures (AU), Silver Futures (AG), Iron Ore Futures (IO), Cotton Futures (CF), Soybean I Futures (YSA), Corn Futures (YC), Power Coal Futures (ZC), Coking Coal Futures (JM), CSI 300 Index Futures (IF), and SSE 50 Index Futures (IH). Detailed statistics of all data are summarized in Tables 1 and 2.

Tables 1—Variables for the Research

Variables	Frequency	Abbreviation	Unit
China Containerised Freight Index	Day	CCFI	Index
Clarksons Average Containership Earnings	Day	CACE	$/day
Shanghai Containerised Freight Index	Day	SCFI	Index
Rebar Futures	Day	RB	Yuan/Ton
Copper cathode futures	Day	CU	Yuan/Ton
gold futures	Day	AU	Yuan/g
Silver futures	Day	AG	Yuan/kg
Iron Ore Futures	Day	IO	Yuan/Ton
cotton futures	Day	CF	Yuan/Ton
Soybean No. 1 Futures	Day	YSA	Yuan/Ton
Corn Futures	Day	YC	Yuan/Ton
Thermal Coal Futures	Day	ZC	Yuan/Ton
Coking coal futures	Day	JM	Yuan/Ton
CSI 300 Futures Index	Day	IF	Yuan
SSE 50 Futures Index	Day	IH	Yuan

Tables 2—Descriptive Statistics for CCFI Forecast Data

Variables	Mean	Std.	Min.	Max.
CCFI	1505.161679	986.809956	743.710000	3587.910000
CACE	29319.807275	27838.211729	8647.518530	87777.946380
SCFI	1894.889701	1492.144342	646.590000	5109.600000
RB	4009.615672	641.769392	2920.000000	5765.000000
CU	55330.485075	9693.864548	38380.000000	74840.000000
AU	336.907239	52.415779	263.800000	450.460000
AG	4380.097015	713.004230	3068.000000	6652.000000
IO	689.212687	200.473637	423.000000	1243.500000
CF	15613.003731	2613.025574	10735.000000	21910.000000
YSA	4564.078358	1086.497636	3139.000000	6463.000000
YC	2180.313433	436.592439	1618.000000	3027.000000
ZC	672.697015	152.422721	494.800000	1647.600000
JM	1574.718284	543.314967	943.000000	3551.000000
IF	4134.270149	614.508576	3003.600000	5748.800000
IH	2923.479851	362.008854	2292.600000	4003.600000

Line graphs for each indicator from March 24, 2017, to May 27, 2022, are depicted in Figures 1 to 16. These charts illustrate the fluctuations of the variables over recent years and serve as a foundation for our examination of the model's outcomes. By utilizing these line charts, we can gain a comprehensive understanding of the periodicity and trends of the indicators, enhancing our comprehension of the current state and future trajectory of the shipbuilding cost market. Additionally, these charts assist in assessing the predictive efficacy of the CNN, LSTM, and CNN-LSTM models, thereby deepening our understanding of the shipping market.

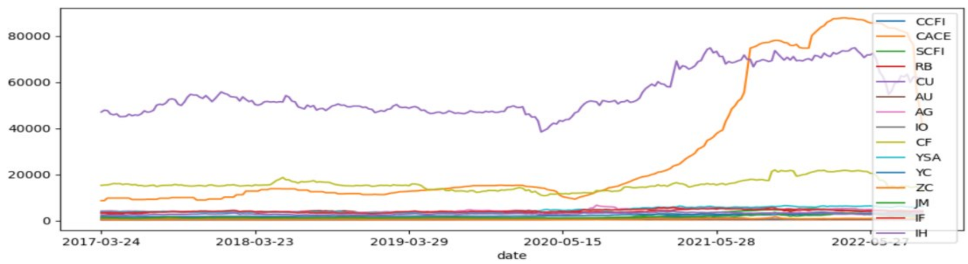

Figure 1. Line Graph of Raw Data for All Data

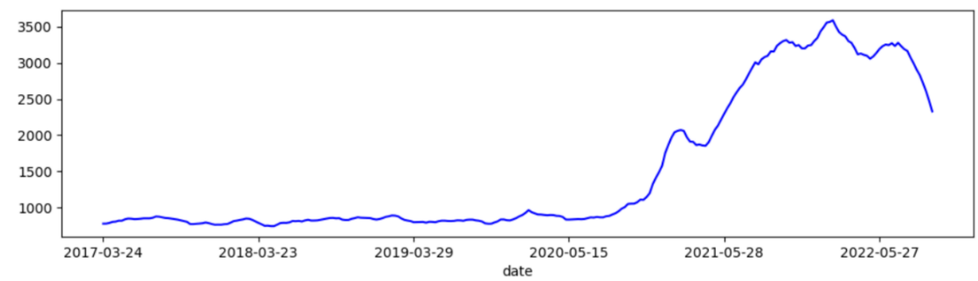

Figure 2. CCFI Raw Data Line Graphs

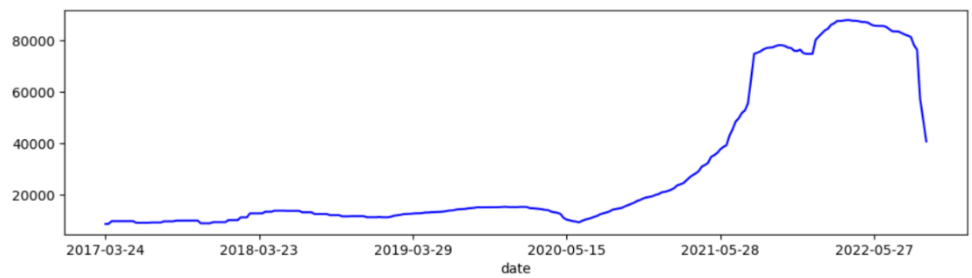

Figure 3. CACE Raw Data Line Graphs

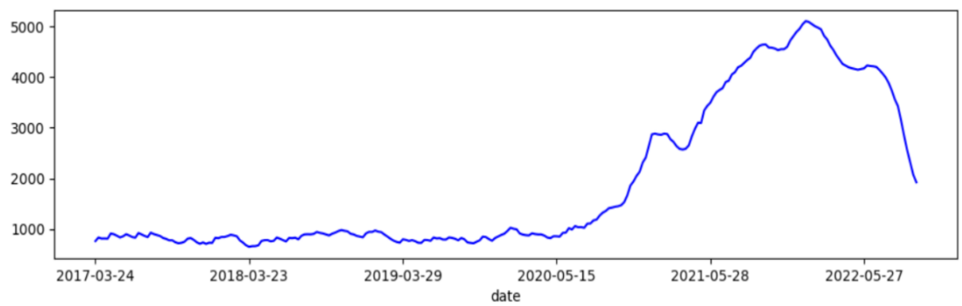

Figure 4. SCFI Raw Data Line Graphs

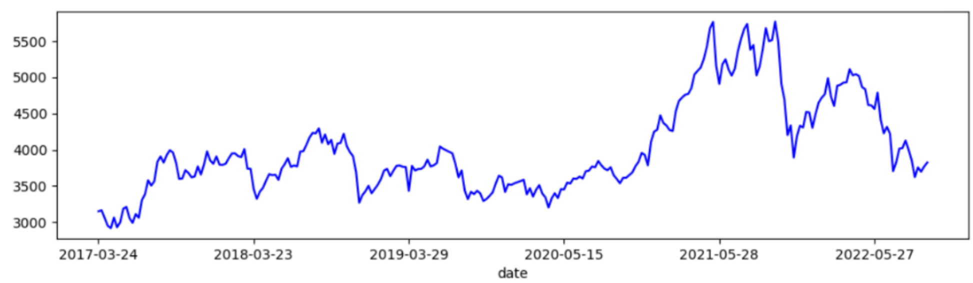

Figure 5. RB Raw Data Line Graphs

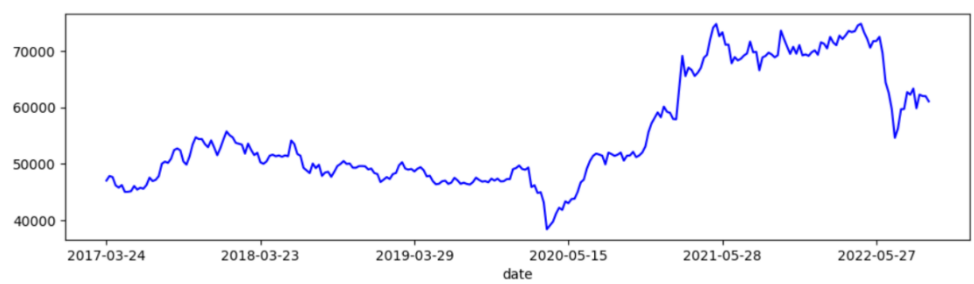

Figure 6. CU Raw Data Line Graphs

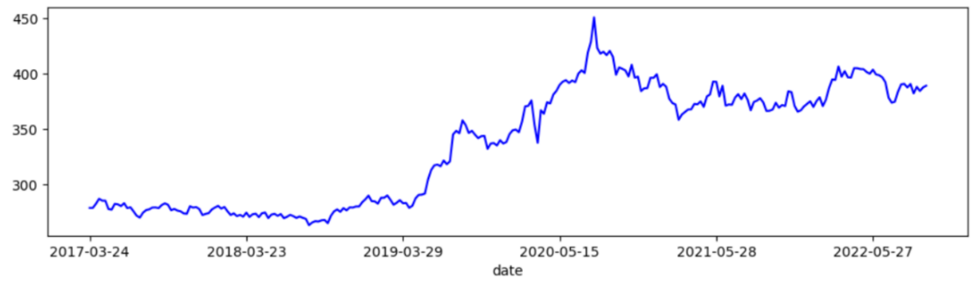

Figure 7. AU Raw Data Line Graphs

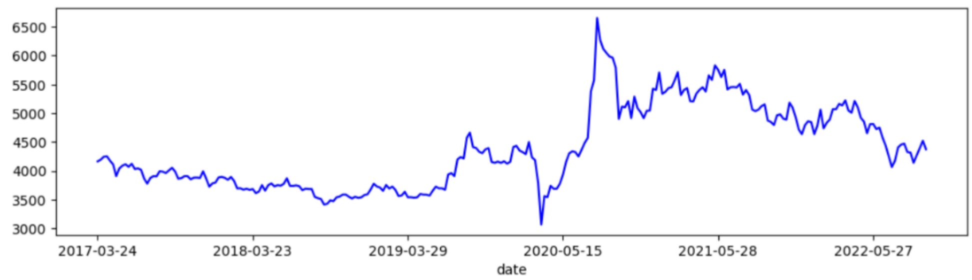

Figure 8. AG Raw Data Line Graphs

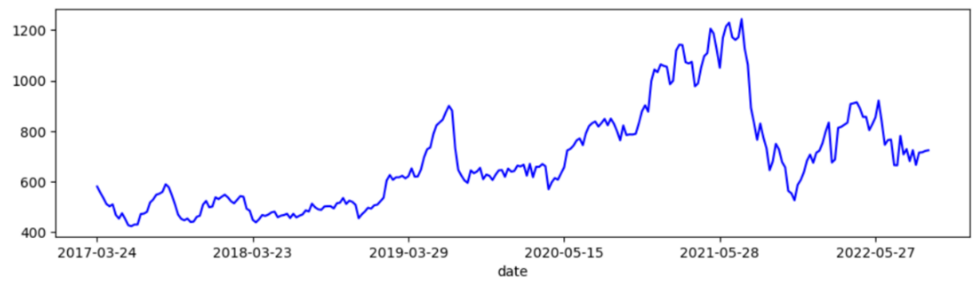

Figure 9. IO Raw Data Line Graphs

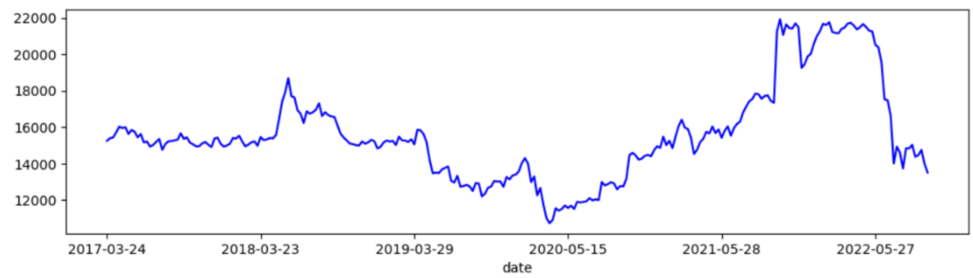

Figure 10. CF Raw Data Line Graphs

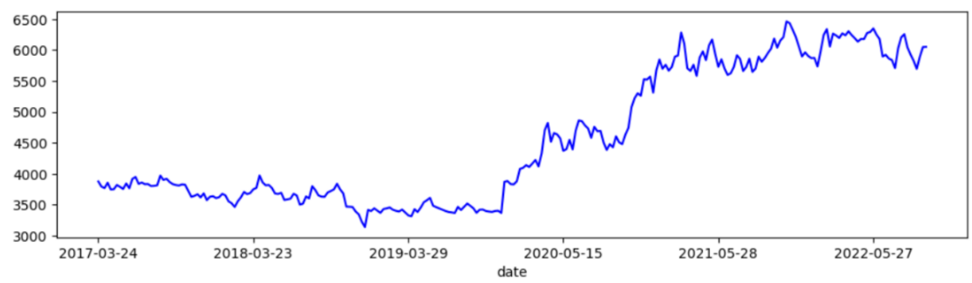

Figure 11. YSA Raw Data Line Graphs

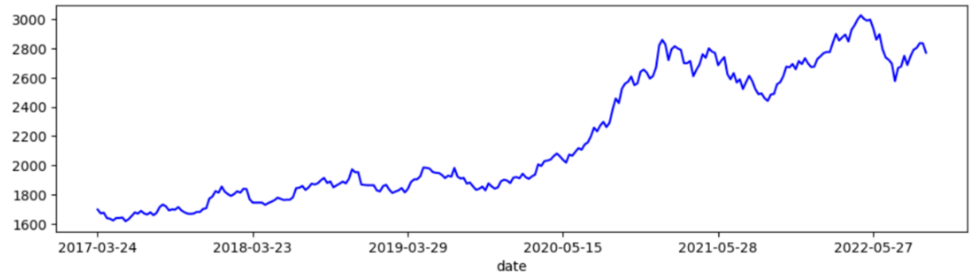

Figure 12. YC Raw Data Line Graphs

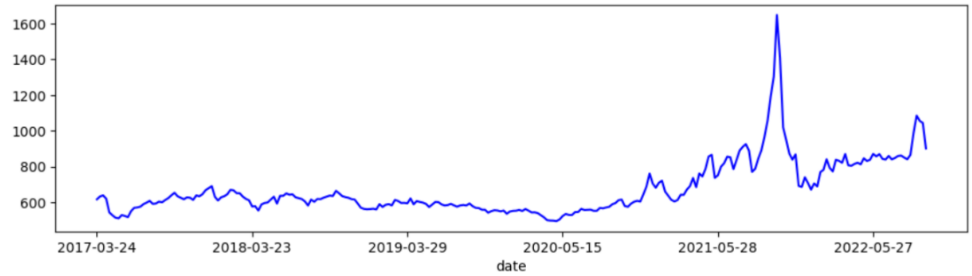

Figure 13. ZC Raw Data Line Graphs

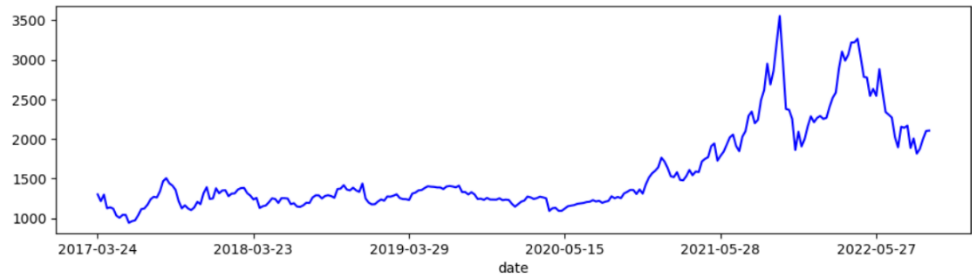

Figure 14. JM Raw Data Line Graphs

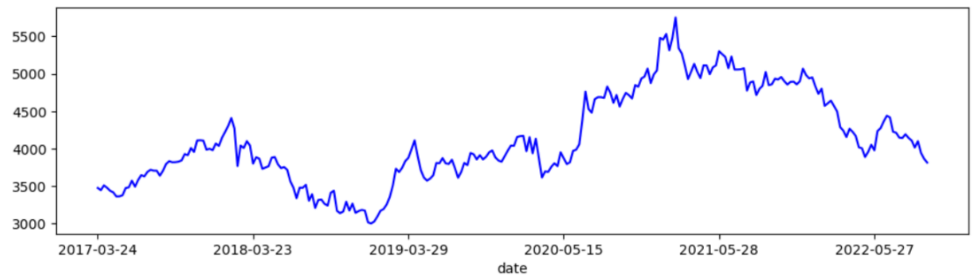

Figure 15. IF Raw Data Line Graphs

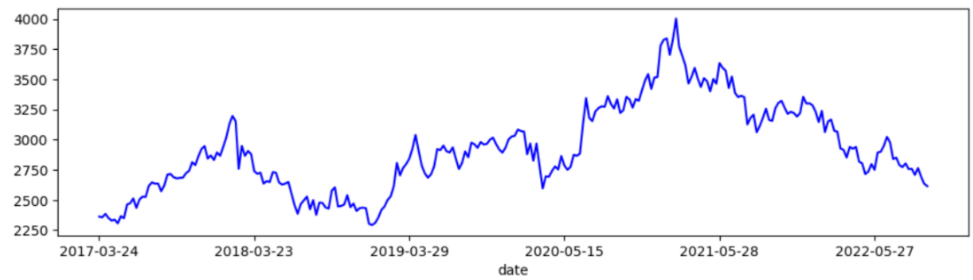

Figure 16. IH Raw Data Line Graphs

In the field of machine learning, correlation is frequently employed as a preliminary technique to identify relationships between variables, which is essential for enhancing the precision of predictive models. A heat map is a graphical representation of the correlation between numerical variables, illustrating the connections among various variables. The value in each cell denotes the nature of the relationship between two entities, with higher values indicating a stronger link and lower values indicating a weaker link. The impact of independent features on intuitive predictions can be determined by examining the positive and negative correlations among eigenvalues. A high positive correlation is typically observed when the Pearson correlation coefficient exceeds 0.7. The correlation among the dataset's features is illustrated in Figure 17.

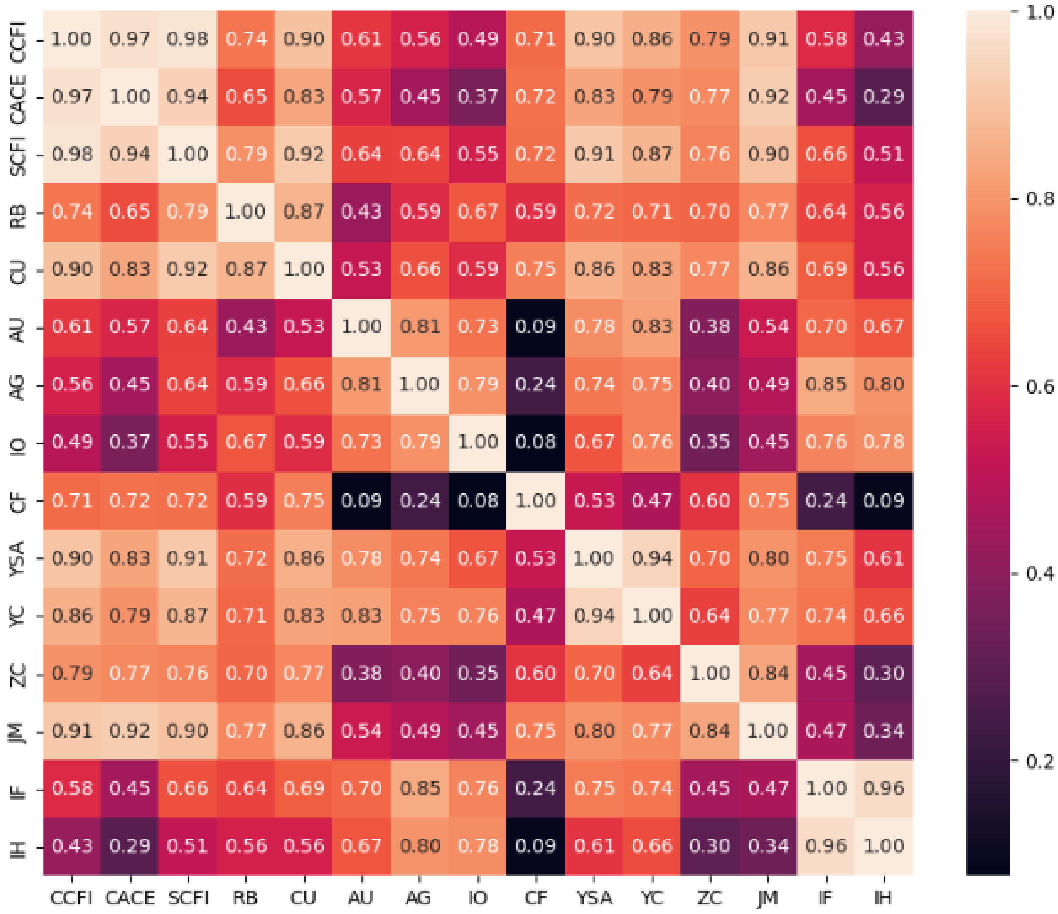

Figure 17. Correlation between data.

3.2 Model

Convolutional Neural Networks (CNN): Prior research has indicated that CNNs exhibit significant potential in resolving time series issues. In the field of image recognition, CNNs have achieved remarkable success. The CNN architecture comprises a convolutional layer, a pooling layer, and a fully connected layer, as illustrated in Figure 18. The formula for extracting features through one-dimensional convolution is represented as follows:

$$(1)a_j^{(l+1)}(\tau) = \sigma\left[b_j^l + \sum_{j=1}^{F'} K_{ij}^l(\tau) \times a_j^{(l)}(\tau)\right]$$

Where. $a_j'(\tau)$:a feature mapping j in layer l; σ :an activation function ReLU; :a bias; :an activation function ReLU b_j^l :a bias; :a number of feature maps on layer F^l :a number of feature maps on layer l feature map f :a convolution of layer feature map K_{if}^l :a convolution of layer l eature map f to create feature map j in layer $l + 1$.

After the convolution process, the pooling layer reduces the dimensionality of the convolution layer output. This effectively decreases the computational load and enhances the robustness of the model. The pooling operation can be defined as follows:

$$(2)A_k^l(i,j) = \left[\sum_{x=1}^{f} \sum_{y=1}^{f} A_k^l(s_0 i + x, s_0 j + y)^p\right]^{\frac{1}{p}}$$

Where f :a convolution kernel size; :one-step length; :one-step length s_0 :one-step length; :a number of filler layers, when p :a number of filler layers, when p infinity pooling region to take the maximum value, that is, the maximum pooling.

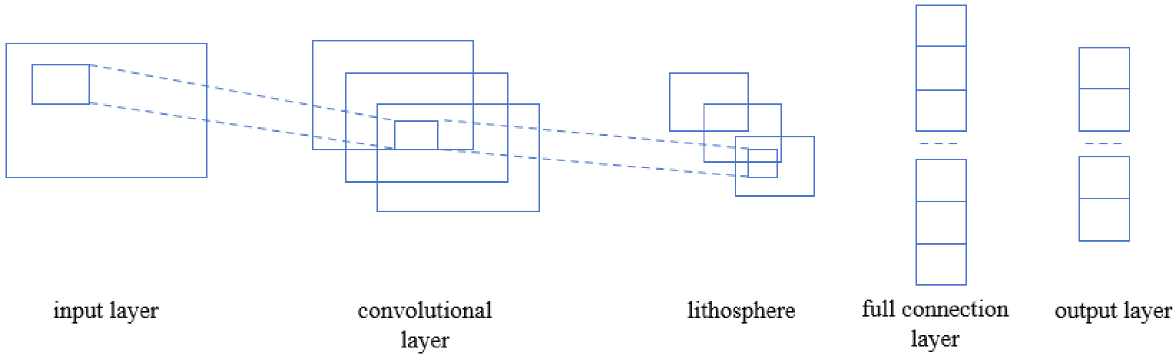

Figure 18. Convolutional neural network structure diagram

Table 3—CNN Final Model Parameters

Layer (Type)	Output Shape	Param#
Input_1 (Input Layer)	[(None, 3, 5)]	0
conv1d (Conv1D)	(None, 3, 32)	512
conv1d_1 (Conv1D)	(None, 3, 64)	6208
flatten_ (Flatten)	(None, 192)	0
dense (Dense)	(None, 128)	24704
dense_1 (Dense)	(None, 32)	4128
dense_2 (Dense)	(None, 1)	33

Notes: Total params: 35,585

Trainable params: 35,585

Non-trainable params: 0

Long Short-Term Memory Networks (LSTM): Long Short-Term Memory (LSTM) networks represent a significant advancement over traditional Recurrent Neural Networks (RNNs), as depicted in Figure 19. They introduce three gated units: the input gate, the forget gate, and the output gate. The forget gate determines which information should be retained or discarded from the cell state, while the input gate selectively incorporates new information into the cell state. Finally, the output gate passes the updated cell state to the next time step. These gated mechanisms enable LSTMs to be more effective than traditional RNNs in storing and retrieving information across long sequences, thus allowing for a deeper exploration of data over extended time spans. Furthermore, LSTMs address the issues of vanishing and exploding gradients, significantly enhancing the model's learning capability and stability.

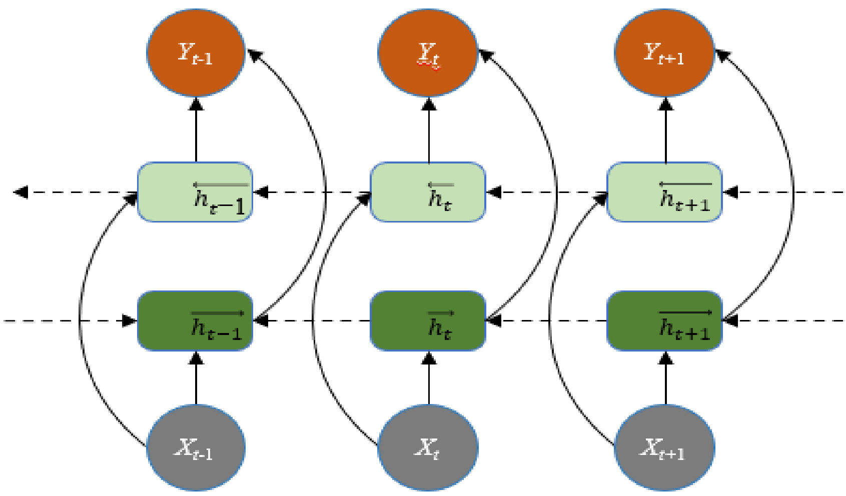

Figure 19. LSTM network structure diagram.

The LSTM network formula is as follows

$(3) f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$

$(4) i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$

$(5) \tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$

$(6) C_t = f_t C_{t-1} + i_t \tilde{C}_t$

$(7) o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$

$(8) h_t = o_t \tanh(C_t)$

where f_t、i_t、o_t are the outputs of the forgetting gate, the input gate and the output gate, respectively; $\tilde{C}_t$ is the cell state at the current moment; C_{t-1} is the cell state at the previous moment; C_t is the updated cell state; W_f、W_i、W_c、W_o and b_f、b_i、b_c、b_o are the weight matrices and bias vectors of the forgetting gate, input gate, current cell state, and output gate, respectively; h_{t-1} is the output of the previous moment; x_t is the input of the current moment; h_t is the final output of the current moment; and σ is the sigmoid function.

Table 4—LSTM final model parameters

Layer (Type)	Output Shape	Param#
Input_2 (Input Layer)	[(None, 3, 5)]	0
lstm (LSTM)	(None, 3, 32)	4864
lstm_1 (LSTM)	(None, 64)	24832
flatten_1 (Flatten)	(None, 64)	0
dense_ 3(Dense)	(None, 128)	8320
dense__4 (Dense)	(None, 32)	4128
dense_5 (Dense)	(None, 1)	33

Notes: Total params: 42,177

Trainable params: 42,177

Non-trainable params: 0

CNN-LSTM Model: The CNN-LSTM model is a deep learning architecture that combines the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs). CNNs excel at processing spatial data, such as images, and extracting local features through convolutional and pooling layers, while LSTMs are adept at processing time-series data and learning long-term dependencies. This combination enables CNN-LSTM models to effectively extract useful information and generate accurate predictions when dealing with complex multidimensional data, such as the CCFI.

The complexity and multidimensional nature of CCFI data necessitate the use of advanced predictive models, such as CNN-LSTM, to effectively extract intrinsic useful information. Through its unique structural design, the model first employs CNN to capture and extract local features of the data, thereby reducing dimensionality while maintaining critical time series information. This prepares the subsequent LSTM network, which leverages its powerful time series processing capability to explore long-term dependencies in the CCFI time series. This model combination not only significantly improves the accuracy of CCFI predictions but also enhances the model's understanding of the complexities inherent in CCFI movements.

In addition, the application of the CNN-LSTM model in CCFI forecasting brings several significant advantages: firstly, it surpasses traditional time series forecasting methods in accuracy, effectively capturing complex patterns and trends in the data, which is crucial for business. Secondly, the model demonstrates robustness to noise and outliers, particularly important in the shipping industry, which is often subject to external factors, thus improving the reliability of forecasts. Furthermore, the model is capable of handling large volumes of data and can be easily extended to accommodate a wider range of datasets, making it well-suited for the dynamic and ever-evolving nature of the shipping and finance industries.

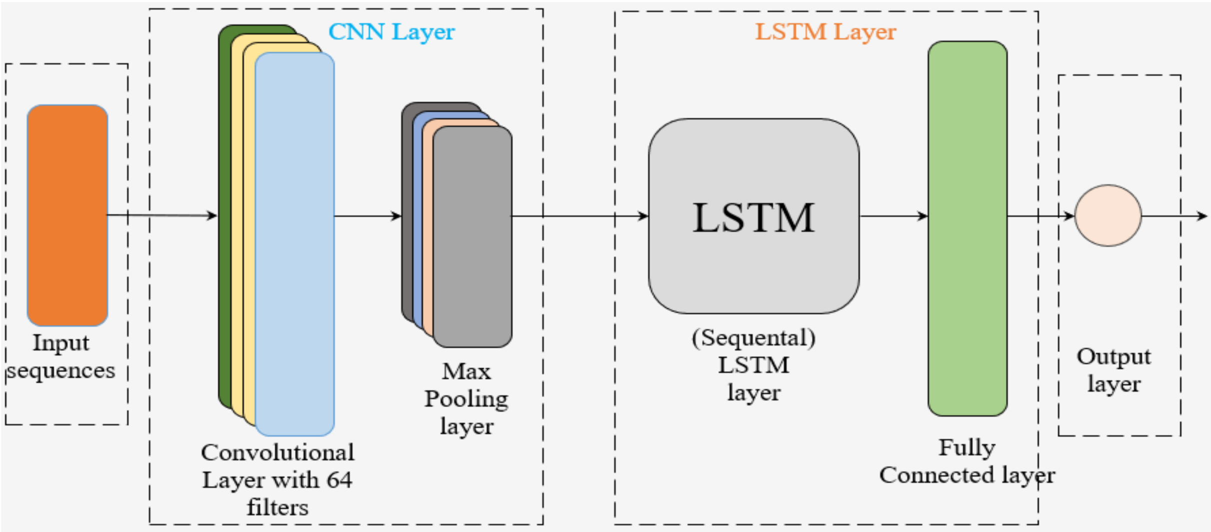

Figure 20. CNN-LSTM Model

Table 5—CNN-LSTM final model parameters

Layer (Type)	Output Shape	Param#
Input_3 (Input Layer)	[(None, 3, 5)]	0
conv1d_2 (Conv1D)	(None, 3, 32)	512
conv1d_3 (Conv1D)	(None, 3, 64)	6208
lstm_2 (LSTM)	(None, 3, 32)	12416
flatten_4 (Flatten)	(None, 96)	0
dense_6 (Dense)	(None, 128)	12416
dense_7 (Dense)	(None, 32)	4128
dense_8 (Dense)	(None, 1)	33

Notes: Total params: 35,713

Trainable params: 35,713

Non-trainable params: 0

4 Results

4.1 Data Analysis Process

In this research project, we conducted a comparative analysis of three distinct models (CNN, LSTM, and CNN-LSTM) to evaluate their effectiveness in predicting the China Container Freight Index (CCFI). The results of the models are represented in a series of graphs, demonstrating their effectiveness in quantifying the loss function as mean squared error (MSE) using data from both the training and test sets. Additionally, the prediction results for the training set, prediction set, and actual values will provide a concise summary of the overall performance comparison.

We began by examining the loss trajectories of each of the three models (Figures 21, 22, 23). The models were evaluated under three distinct scenarios: underfitting, appropriate fitting, and overfitting, utilizing the aforementioned trajectories as metrics. Underfitting is indicated when the validation loss exceeds the training loss. Conversely, overfitting is characterized by a substantial discrepancy between the validation and training losses, or by an upward trend in the validation loss. The convergence of the training and validation loss curves is indicative of an acceptable fit. The x-axis represents the number of iterations, while the y-axis displays both training and validation losses. The training loss is symbolized by a blue line, while the validation loss is visually represented by an orange line.

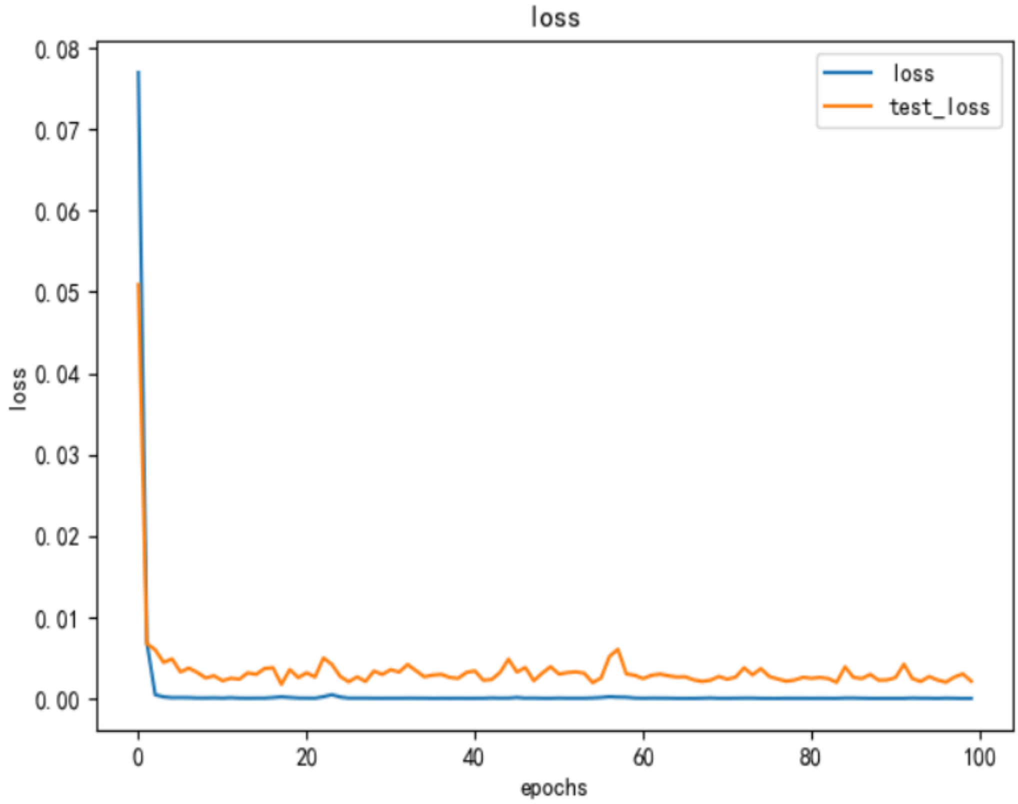

Figure 21. CNN Loss Curves

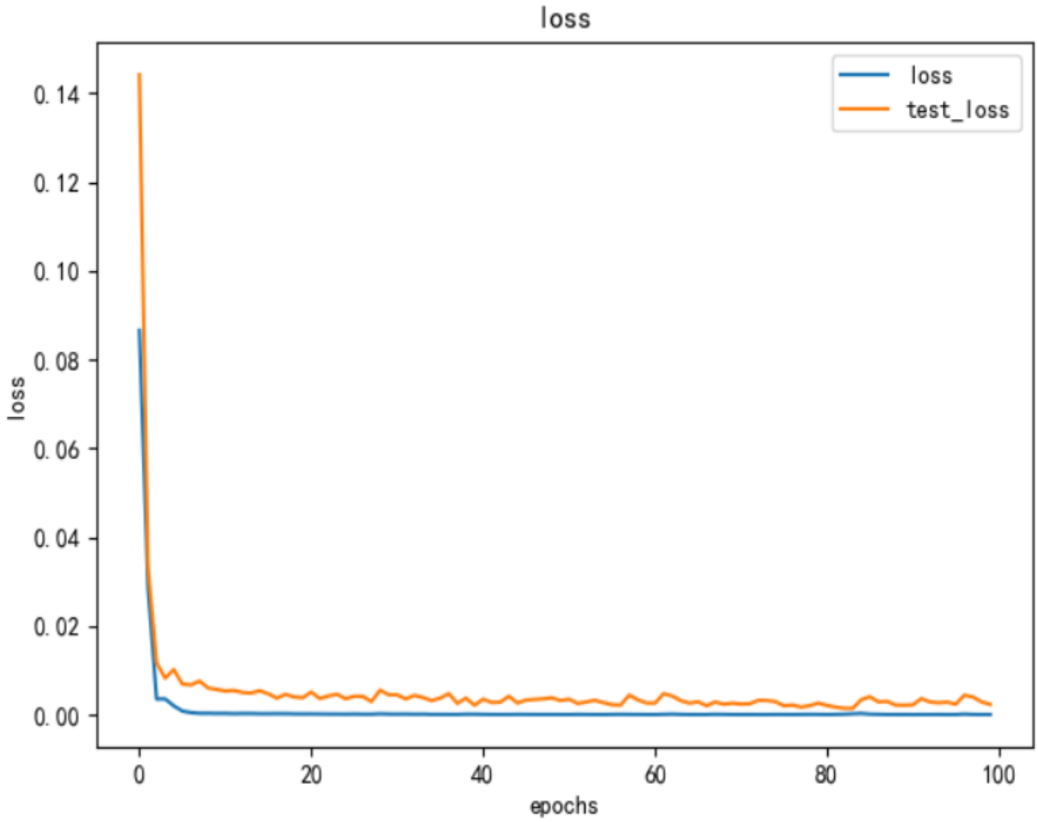

Figure 22. LSTM Loss Curves

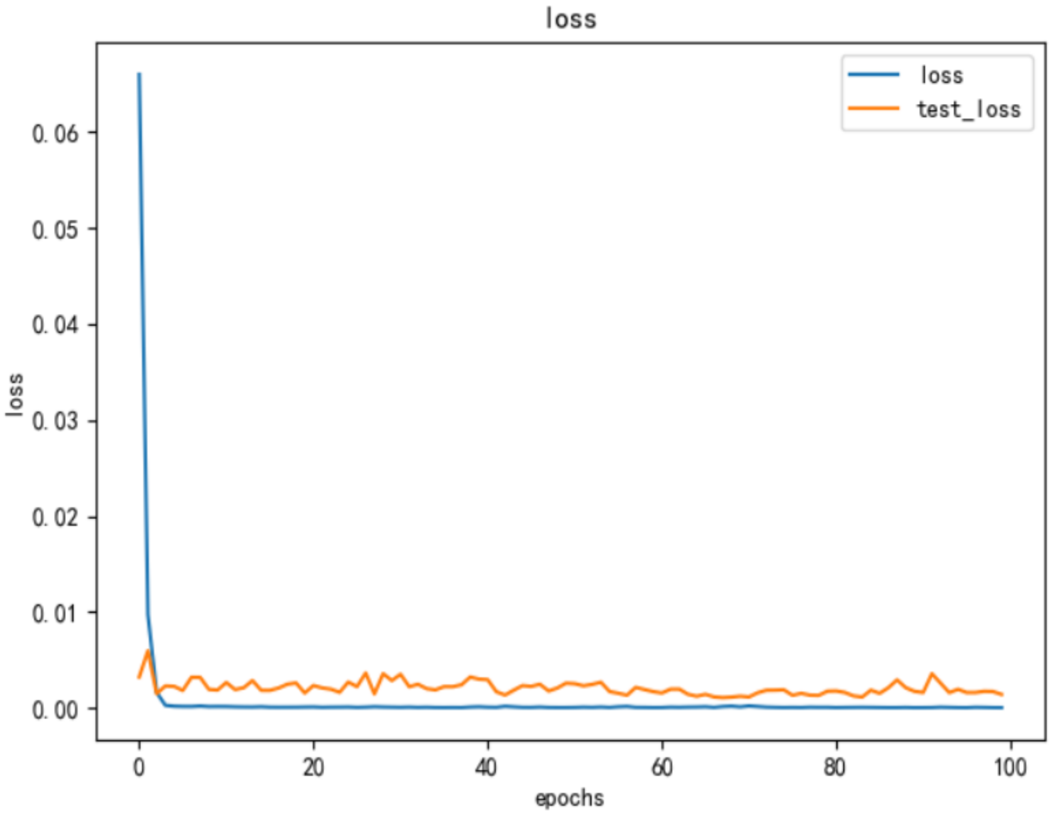

Figure 23. CNN-LSTM Loss Curves

To provide a succinct summary of the overall performance comparison, we compiled the prediction outcomes for the CNN, LSTM, and CNN-LSTM models on both the training and test sets, including the actual values (see Figures 24, 25, and 26). The CNN-LSTM model exhibits the most favorable performance, as evidenced by the results in Figure 26. In our research, we implemented a rigorous data handling protocol that included three distinct phases: validation, training, and testing. Each phase is essential for assessing the CNN-LSTM model's performance. The dataset was distributed among these three subsets in a 9:1 ratio, ensuring a sufficient amount of data for training while preserving a valid testing set to evaluate the model's generalizability and accuracy. The model's capacity to generalize to unseen data is enhanced by its increased ability to learn from diverse instances, achieved by utilizing a larger portion of the dataset for training. Although the validation and test sets are smaller in size, they are crucial for evaluating the model's accuracy and robustness, ensuring that the model is not only precise but also dependable in real-world scenarios.

The data was partitioned temporally, with each subset selected from consecutive time windows. Data from the earliest time points was included in the training set, allowing the model to learn from historical information. The validation set was formed from a subsequent time window, enabling the model to adjust to temporal changes not present in the training data. The model's future prediction capabilities were unbiasedly evaluated by incorporating data from a later time window into the testing set. The models were able to generate predictions for multiple future time steps by employing a multi-step ahead forecasting approach, which is essential for time series data. However, it is widely recognized that the efficacy of deep learning models such as CNNs and LSTMs can be compromised by extended forecasting horizons. To mitigate this issue, we implemented a sliding window prediction method, which involved training and validating the model on shorter subsequences to ensure robustness. Figure 26 demonstrates that the CNN-LSTM model outperformed the CNN and LSTM models in terms of forecasting ability and accuracy. This suggests that the CNN-LSTM architecture effectively captured the intricate temporal dependencies in the data, thereby improving the model's capacity to generate reliable multi-step forecasts.

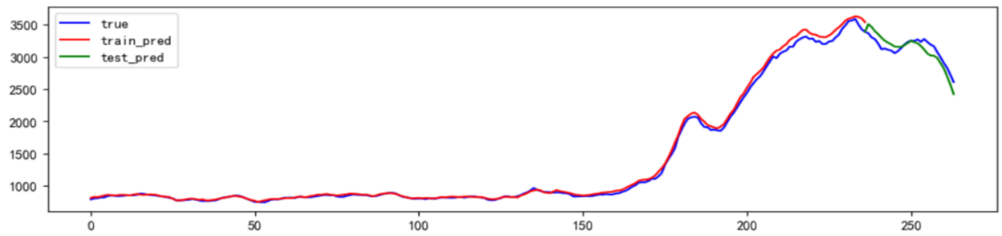

Figure 24. CNN Comparison of raw data, training process and testing process

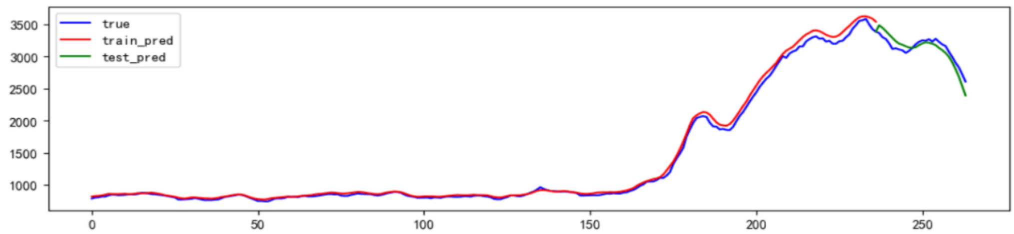

Figure 25. LSTM Comparison of Raw Data, Training Process and Testing Process

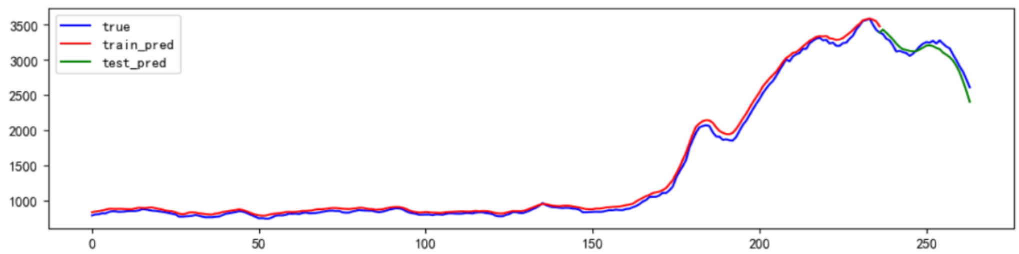

Figure 26. CNN-LSTM Comparison of Raw Data, Training Process and Testing Process

4.2 Model Assessment

As evaluation metrics, we utilized the mean squared error (MSE) and the coefficient of determination (R^2). The following are the mathematical expressions that represent these metrics.

$$\begin{aligned} \mathrm{MSE} &= \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_l)^2 \\ R^2 &= 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_l)^2}{\sum_{i=1}^{n}(\bar{y}_l - \hat{y}_l)^2} \end{aligned} \tag{9}$$

Notes. y_i is the true value; is the predicted value; $\hat{y}_l$ is the predicted value; is the average value. $\bar{y}_l$ is the average value.

After completing 100 simulation iterations, the mean R^2 scores for the three models across the training and test datasets were computed. The comparative analysis presented in Table 6 illustrates that the CNN-LSTM integrated model exhibits superior performance, as evidenced by its R^2 value of 71.68%.

Tables 6—Model Performance Comparison

Model	MSE	MAE	R^2
CNN	14135.560405	104.764020	0.538402
LSTM	11651.239342	96.082811	0.619528
CNN-LSTM	8673.962229	82.605941	0.716751

5 Discussion and Conclusions

The China Containerized Freight Index (CCFI) is a pivotal indicator of the shipping industry, international trade, and the global economy. Establishing an accurate CCFI forecasting model is a valuable tool and prerequisite for effective shipping management, investment, and production planning (Bandyopadhyay & Rajib, 2023). This study aims to enhance the accuracy of CCFI forecasting by developing an advanced model and applying it to actual operations in the shipping and financial industries.

The findings of this investigation indicate that to improve the precision of CCFI predictions, we implemented a combination of CNN, LSTM, and CNN-LSTM methodologies tailored to CCFI characteristics. Utilizing a total of 29,308 observations from 24 March 2017 to 27 May 2022, we assessed the predictive capabilities of the proposed model using daily big data. The results demonstrate that the optimized CNN-LSTM integrated model possesses significant advantages over the CNN and LSTM models. The model's structure is objectively determined based on the performance of the validation set, revealing hidden nonlinear features in CCFI predictions. Furthermore, the model accommodates random sample selection, data frequency, sample structure breaks, and considers candidate hyperparameters, memory length, input variables, and training set size. Our comparative analysis shows that the CNN-LSTM model is adept at accurately identifying and predicting patterns in complex data, as evidenced by an R^2 value of 71.68%, surpassing the individual R^2 values of the CNN and LSTM models. This indicates a relatively consistent fit with the fluctuations in CCFI.

5.1 Theoretical Contributions

This paper makes substantial and multifaceted contributions to the field. Firstly, it advances the body of research on machine learning applications in finance and shipping. The utilization of three machine learning models not only provides a more precise forecasting tool for the shipping market but also establishes an analytical framework for examining the interaction between the shipping and financial sectors. Although scholars have shown interest in forecasting CCFI (Kang & Yoon, 2019), there remains a lack of research integrating CNN, LSTM, and CNN-LSTM within the context of the Chinese commodity futures market for CCFI predictions. Consequently, it is crucial to investigate the significance of the Chinese futures market in forecasting CCFI using machine-based modeling. Financial investors can make more informed decisions and accurately identify investment opportunities by understanding and forecasting CCFI trends. Similarly, maritime market participants, including shipowners and shipping companies, can better manage risk and allocate capital by comprehending the potential impact of the financial market on their operations. Our machine learning research not only provides novel insights into the complex dynamics of the global shipping market but also highlights the relationship between the real economy and financial markets.

Secondly, by integrating CNN and LSTM models, we demonstrate that the combined CNN-LSTM model exhibits superior predictive capability compared to individual models. CNNs are primarily focused on processing spatially hierarchical data, while LSTMs excel in learning time series data. The integrated CNN-LSTM model is well-suited for managing data that is both spatially and temporally stratified, which is essential for predicting complex time series data like CCFI, influenced by various factors. This research thereby enhances the prediction accuracy and robustness of CCFI and builds upon the work of Munim and Schramm (Kang & Yoon, 2019), offering new perspectives on the relationship between CCFI and a diverse array of complex futures prices.

5.2 Management Contribution

The managerial implications of predicting trends in CCFI are significant. Initially, logistics companies rely on accurate shipping price information to create cost budgets and transport plans. By examining CCFI, logistics companies can forecast fluctuations in shipping prices, enhancing service quality, reducing costs, and optimizing transport routes and cargo loading strategies. Moreover, logistics companies can leverage CCFI information to mitigate transport cost risks by securing transport costs through financial instruments like futures contracts, thus preventing losses from price fluctuations.

Secondly, the shipping market's volatility makes it challenging to anticipate market risks. This research assists investors and shipping companies in identifying market risks and developing effective risk management strategies. For instance, shipping companies can use CCFI forecasts to rationally organize container leasing, maintenance, and management, thereby mitigating the impacts of market fluctuations. Investors can monitor CCFI forecast trends and adjust their investment portfolios to diversify risks at appropriate times.

Lastly, this investigation serves as a crucial resource for government bodies concerning the financial operating conditions of the shipping market. By monitoring CCFI forecasts, the government can timely evaluate market dynamics, investigate container-related pricing strategies, and develop policies that promote the healthy development of the shipping industry. Additionally, this research contributes to enhancing the overall competitiveness of the industry, facilitating the deep integration of the shipping and financial markets, and supporting the stable and sustainable development of both sectors.

6 Limitations and Future Research

Our research presents several limitations that suggest directions for future work. The predictive capabilities of the CNN, LSTM, and CNN-LSTM models may be constrained by the specific datasets and parameters employed during training. Hyperparameter selection significantly influences model performance; thus, future studies could benefit from implementing automated hyperparameter optimization techniques to enhance efficiency. Furthermore, this study did not explore other high-performing machine learning models, leaving an opportunity for future research to investigate whether the incorporation of additional models could improve predictive accuracy.

Another area for improvement involves the inclusion of additional market factors and external variables to refine the models' predictive power, as multi-factor forecasting represents a promising approach. The integration of expert evaluation methods could further bolster these forecasts, leading to more precise outcomes. Additionally, further clarification is needed regarding data preprocessing procedures, including how missing values were addressed, the normalization techniques utilized, and the feature selection process. A more transparent explanation of the division between training, validation, and test datasets would enhance the reliability of model evaluation.

The inclusion of more comprehensive visualizations, such as error distribution charts and comparisons between predicted and actual values, could provide deeper insights into model performance. Future research should focus on a more detailed analysis of why models like CNN-LSTM outperform others in predicting the China Containerized Freight Index (CCFI), aligning these findings with existing literature. Moreover, the practical implications of these results, particularly in their application to decision-making and risk management in the shipping industry, should be emphasized further. Finally, the study should address limitations related to sample data, model selection, and the impact of external environmental factors on predictions. Future work should explore the adaptability of these models to varying market conditions and consider integrating expert insights to enhance the practical utility and accuracy of the predictions.

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